Advancing UAV Autonomy Through Neurorobotics with Hippocampal-Inspired Cognitive Mapping and Route Planning Algorithms

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Abstract: The ability of autonomous unmanned aerial vehicles, also known as UAVs, to do dangerous and monotonous tasks in lieu of people has made them an integral part of contemporary aeronautical engineering. First and foremost, it is important to highlight their widespread use in vital sectors such as disaster relief (e.g., transporting medical supplies to impacted areas, focusing on legitimate targets during wartime, etc.), surveillance, and environmental monitoring. These sectors offer optimism for the future of aviation, as unmanned aircraft are more efficient, effective, and secure than human pilots. However, there is still a significant gap between the decision-making capabilities of green systems and UAVs, even if all present efforts are focused on making UAVs more autonomous via the integration of flexible navigation algorithms. First, the existing techniques, which vary from traditional pathfinding to optimizations based on biological principles, are inadequate when faced with real-world environments that need rapid, efficient changes. Finding and closing the gap between the navigational skills of the human brain and those of AI algorithms is the primary goal of this research. To achieve this goal, we introduce the Hippocampal Route Planner (HRP), a neurorobotics design inspired by the navigational abilities of the mammalian hippocampus. UAVs are able to naturally sense their surroundings and navigate in real time thanks to the HRP algorithm. In other words, UAVs equipped with the HRP algorithm may mimic the mental maps seen in living things. We have tested our model in air supremacy, and it outperforms other models with less CPU overhead and power consumption and more successful runs. What makes the HRP algorithm so impressive is its ability to learn and make judgments over time; this is perhaps the most astounding feature of all of them. With scalability and efficiency in mind, there's a better likelihood of widespread adoption across industries, which will boost airborne operations' safety and dependability.

Keywords: *Autonomous UAVs, Neurorobotics, Hippocampal-Inspired Algorithms, Cognitive Mapping, Route Planning Algorithms, Advanced Navigation Systems*

1. INTRODUCTION

Introduction of UAVs has really marked off a dizzy era of engineering, utilizing incredible technology to drive without requirement of the human controls. These sophisticated machines have been used to perform tasks incorrectly for human beings [1]. For example, operation by machine could be too dangerous or monotonous. Such operations can include disaster response, surveillance monitoring, and general environmental monitoring [2]. The convenience of self-driving UAVs relies on reshaping operational efficiency, safety, and the cost effectiveness factors, that, in turn, place them in the spotlight as an innovative type of aircraft, not manual. The forthcoming study in this area is designed to support UAVs technological solutions that will possess the ability of self-adapting dynamic intelligence in response to ever changing environment conditions, and will be used for mission objectives of complex nature. On the contrary the gap between nowadays UAV capabilities and those of living creatures which are hardwired for such complexity as improvisation in diverse tasks with the highest degree of their cognitive and navigational autonomy remains widening.

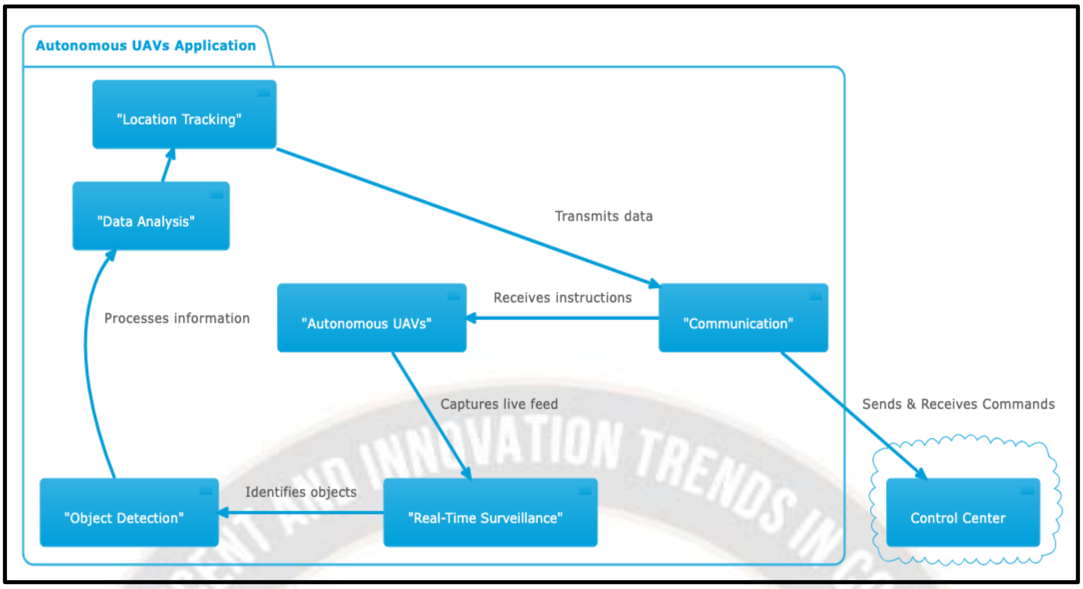

Fig. 1 Workflow of Autonomous Unmanned Aerial Vehicles

As the network map displayed in the Fig. 1 shows, the harnessed autonomy level of UAVs used in a real time surveillance and monitoring purposes becomes more complex. The grounds of the system can be expanded to achieve endless possibilities with complementary UAVs which accompany with advanced cameras and sensors. They are able to transmit real-time videos of their environment with no lag that supports UAVs to perform their tasks without any interruption. This live feed transfers in processing objects detection algorithm, which need capabilities of detecting and classifying various objects that are in the field of vision of UAV. During this subsequent data analysis phase, we sift out helpful information such as trends, patterns and actionable intelligence that may aid in the targeting of policy interventions and improved service delivery. At the same time, location tracking receives the information of relevant objects' movements and visualizes them as the trajectory of objects, providing the prediction of future location. At the end of this process, there will come the stage where the transmitted data are processed by the high-level systems according to the innovated control decision and then through high communication channels they are fed back to the central Control Center. While this area of research has covered numerous methodologies indeed, one can distinguish the principal algorithmic calculus comprising of Dijkstra's and A* algorithms on the one hand and, on the other hand, incorporates the nature-inspired techniques such as Ant Colony optimizations and Genetic Algorithms [3]. Consequently the application of above mentioned techniques is a success in their field. But the constraints come in the arena of real-world fight where the fast adaptation, data synthesis, and saving of energy are important. In those aged methods, the complex real time data assignment and integration will normally be a problem and may as well not be the most appropriate when principle level thinking is necessary and a quick decision has to be made. The approach taken in our research is tackling these complex issues, introducing a novel Robotics Neuron-Platform incorporating human-like navigation, symbolized by the original Hippocampal Route Planner (HRP). The HRP algorithm draws on the nature of the mechanism present in the mammalian hippocampus, which is responsible for assisting in the building and utilization of dynamic cognitive maps for instantaneous movement tracking and decision-making coordination. Such, methodology entrusted the UAVs with the ability to make sense, and respond accurately and reflexive in a manner that is similar to the way biological creatures operate. Advocated for infrastructure drastically diminishes both computational burden and showed energy conservation where at the same time success rates get higher. It obviously exceeds efficiency of extant structures in the fierce environment of simulations. Our research is distinctive in the magnitude of the constraints in current UAV navigation systems that our research is committed to superseding. Being able to establish environment site learning as well to work out autonomous and intelligent decisions on the fly is a sign that robotics is ready for the next step in UAV autonomy. Our system's scalability and its operational efficacy leave little doubt to its diverse scope of industrial applications, which is devising the era of more severe, reliable, and autonomous ways of airborne works. This research not only serves as a valuable academic contribution but also bears significant practical implications, potentially catalyzing a new epoch of sophisticated UAV applications.

International Journal on Recent and Innovation Trends in Computing and Communication
ISSN: 2321-8169 Volume: 11 Issue: 11
***Article Received:** 25 July 2023 **Revised:** 12 September 2023 **Accepted:** 30 November 2023*

2. LITERATURE SURVEY

An overview of the many cutting-edge algorithms and uses of UAVs in a variety of industries, including agricultural, autonomous systems, medical assistance, and more. A closer examination of a few of them is presented here: Within a UAV-empowered Mobile Fog Computing (MFC) system tailored for Medical Internet of Things (IoT) devices, Asim et al. (2023) provide a new approach for optimizing simulated annealing trajectories [4]. Efficient communication and service delivery in medical contexts are presumably the goals of this algorithm, which optimizes the trajectories of UAVs. In their discussion of UAV control using propulsion models and acoustics, Kawamura et al. (2023) go into a hierarchical blend of specialists. The use of acoustic signals for navigation and control, in conjunction with expert systems for UAV dynamics management, could lead to an increase in the autonomy and accuracy of UAVs operating in complicated situations [5]. In their 2023 study, Sánchez-Fernández et al. analyze how autonomous UAV systems might be used in farming, with a focus on reducing drift in fruit orchards. In order to reduce waste and environmental effect, they probably investigate how UAVs [6] can precisely administer treatments like fertilizers or insecticides. A multiple-UAV architecture [7] for autonomous media creation is described by Mademlis et al. (2023). This architecture might include a number of UAVs cooperating to take pictures and videos from different perspectives, which would improve the efficiency and quality of media production. To identify uncertain misleading targets with the help of autonomous dual UAV systems, Salameh et al. (2023) use a federated reinforcement learning strategy [8]. In military or security contexts, this might imply that UAVs are taught to detect and follow objects employing deceitful strategies via the use of distributed learning algorithms.
Using destination-aware fan-shaped clustering, Dixit and Singh (2023) [9] provide BMUDF, a bio-inspired model for fault-aware UAV routing.

To improve routing efficiency and resilience, particularly in the face of errors or failures, this approach seems to integrate biological patterns into UAV flight pathways. The 3DVFH* (3D Vector Field Histogram*) method is a local obstacle avoidance system [10]. Thomessen et al. (2023) provide an adaptation to the algorithm that changes altitude in a bio-inspired way. This upgrade might improve UAVs' ability to navigate in three-dimensional space by letting them dynamically adjust their altitude in reaction to obstructions [11]. Maraveas et al. (2023) use patterns and methods discovered in nature to improve agricultural operations via the use of UAVs [12]. They utilize bio and nature-inspired algorithms in agricultural engineering. Path planning using UAV swarms in obstacle situations is described by Puente-Castro et al. (2024) as a method based on Q-Learning. A swarm of UAVs may be guided across complicated settings using this reinforcement learning method, which most likely maximizes their aggregate navigational abilities. The Rapidly-exploring Random Tree (RRT) technique, developed by Kelner et al. (2024) and used to describe UAV swarm flight trajectories [13], is a way to explore non-uniform regions effectively by constructing a space-filling tree. Situations where the outcome is uncertain and subject to change are ideal for this method. An enhanced sand cat swarm optimization for moving target search by UAV is created by Niu et al. (2024). This system, which takes its cues from sand cat hunting techniques, may help unmanned aerial vehicles (UAVs) find moving or changing targets more quickly and efficiently [14]. To describe the flight paths of UAV swarms, Kelner et al. (2024) use the Rapidly-exploring Random Tree (RRT) technique. Renowned for its fast search and navigation capabilities, the RRT method [15] constructs a tree that covers the search space at random. Because it enables rapid, decentralized decision-making and adaptation to new or changing situations, this may be very helpful for UAV swarms.

In order to facilitate the joint search for lost tourists by Human-UAV teams, Xu et al. (2024) [16] provide an iterative greedy heuristic. It is quite probable that this method is iterative, meaning it continuously improves the search process by improving search patterns. A joint effort between people and UAVs would allow the former to cover more ground and the latter to make more nuanced decisions depending on the circumstances. The loading, mission abort, and rescue site selection procedures for UAVs are the subject of a combined optimization issue that Zhao et al. (2024) devotes their attention to [17]. All three levels of UAV mission optimization—logistical, operational, and emergency—are considered here. In times of crisis or rescue, when quick judgments taking into account many goals are required, this form of optimization is vital. For the purpose of seeking moving targets with UAVs, Niu et al. (2024) provide an enhanced sand cat swarm optimization method [18]. It is quite probable that the sand cat swarm optimization method takes its cues from the sand cat's renownedly effective and secretive hunting style. This strategy has the potential to enhance the UAV's real-time search pattern adaptation capabilities, making it easier to find objects that are in motion. By offering fresh perspectives on old challenges, all of the surveys help advance UAV research. Natural process inspiration drives the algorithms they cover, which aim to improve UAV capabilities in areas like search efficiency, trajectory planning, and difficult scenario decision-making. The computational efficiency, efficacy in real-world

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situations, flexibility to dynamic environments, and capacity to operate in collaborative settings with other UAVs or human teams would likely be the criteria used to assess these investigations. These algorithms aim to improve the autonomy, reliability, and efficiency of unmanned aerial vehicle (UAV) operations for various uses. In order to improve UAV navigation, autonomy, fault tolerance, and job execution, the algorithms used often take models from biological systems. Metrics including computing cost, efficiency, accuracy, fault tolerance, and real-world application are usually used to compare these approaches.

3. METHODOLOGY

Among other things, UAVs are perfect for surveillance, agriculture, and emergency management when these applications are not purely military. Autonomy and AI-based neurorobotics—the topic that involves unique combination of neurology, robotics, and AI—should be considered as the dominant techniques for UAVs operation. This research comes with a new concept of neuro-robotic based UAV navigation that instinctively responds like a pro-organism. Emulating neural networks structure in a UAV control system for autonomous operation makes robots act like advanced ones in terms of the perception and the framework of cognition. In this system the 'real-time sensory data collection architecture' realizes environmental mapping based on both high fidelity environmental data and detailed obstacle detection. From here-on, the sophisticated neural processing unit evaluates flight control, energy managements, and reactive functions to environmental inputs. Integration of AI into UAV operation makes possible good performance of robotic rigs without human participation in complex tasks, creating more compact and safe environment in difficult situations.

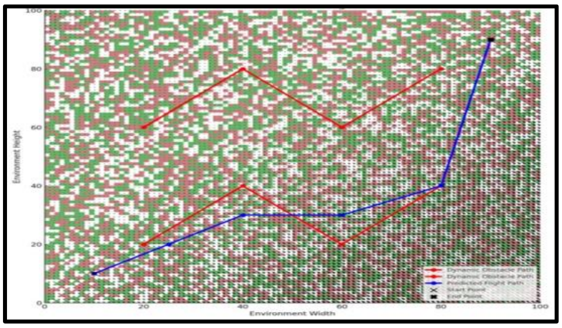

Fig. 2. Enhanced UAV Autonomous Navigation Simulation

The given Fig. 2 represents a subprocedure of autopilot navigation simulation system of a UAV. Multiple layers of detailing form a plane which is a ground for UAV depicted in this cover. Brown regions reflect the contrast that is on the high ground or complex terrain. Symbols indicating wind speed and direction based on arrow shapes. Vector field-in this sense, represents those and other physical factors that the UAV should take account while in the air. In an HTML world, they would be classified as users, transparent as "red lines with points". UAVs have to recognize these objects in real-time and prevent collisions with them. So, they use sensors, LIDAR, cams etc. That beautiful blue line plotting the UAV's flight route, however, has taken into account topography, wind and obstacle circumstances. The same establishes using neurorobotics algorithms, the UAV does on-the-fly route optimization. The aircraft lifts off the black dot and shoots towards the black "X". Neurorobotics systems, especially for UAVs, can deal with unpredictable and dynamic environments, thanks to their ability to process and synthesise diversity in the input data. The Fig. 3 explains that the UAV's state variables, namely altitude speed, and battery level, fluctuate with the dynamics of the environment over time.

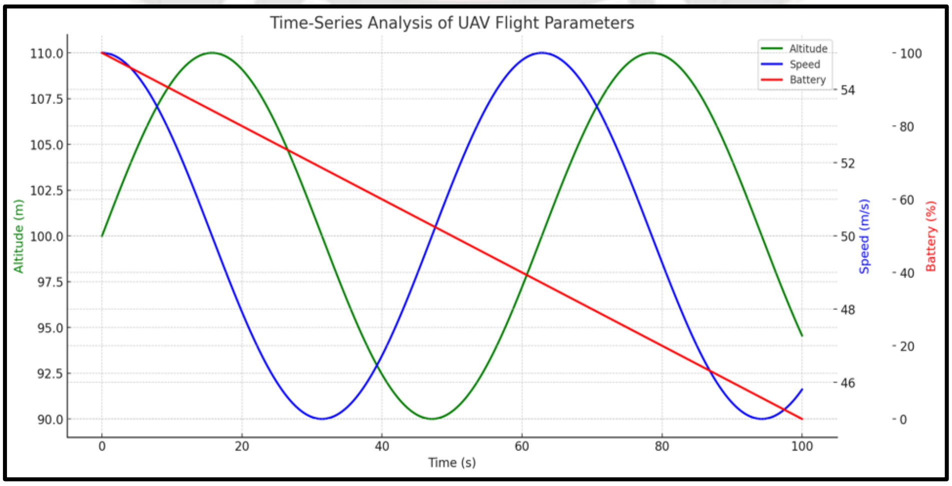

Fig. 3. Time Series Analysis of UAV Flight Parameters

a) Integration with Hippocampal-Inspired Cognitive Mapping:

The composition of the spatial awareness in the UAVs vehicles is basically done by means of cognitive mapping, a characteristic of animal hippocampus, which gives the ability to create the spatial navigation and the memory formation. This research utilizes hippocampal-like algorithms in a method that involves the creation of cognitive dynamic maps, which can have UAVs, through novel ways of understanding and interacting with environmental information, never-before achieved capabilities. The algorithms are built to mimic the hippocampal structure, and the generated spatial representation is created from the input sensor data with its creation an illusion of the environment as the coherent space. Cognitive maps are not static that is why they evolve with every new information, letting us know that the newer knowledge is updated and theoretical path is corrected. It is essential for these systems to be able to gather and process real-time data when working in dynamic or the GPS-denied environments where pre-existing maps are not correct now. The hippocampal-inspired models are fed on huge datasets of environmental interactions and machine learning methods to ensure that UAVs are able to understand their surroundings better akin to brain; which is again as good as natural intelligence.

The quest for creating spatial awareness in UAVs culminates with the application of cognitive mapping which is an oxygen molecules field created by mammals due to the great contribution of the hippocampal formation. The similarity between setting up a coordinate system and finding directions in a new place leads to the need for a mental map of navigation, spatial information processing and memory consolidation. We apply the best practices of hippocampus-styled algorithms to design cognitive maps that have the ability to respond to external stimuli by using changeable interpretations and actions towards the current environments. The 'computational hippocampal model' is at the core of our approach and comprises a set of algorithms that simulate a natural hippocampus' function. We have the following key components in our models: The second one is the Spatial Temporal Cells Simulation that demonstrates the memorization of a sequence of events (episodes) or movement (trajectories) from the brain. This model is mimicking cell N_i by the help of artificial neuron system. It should be noted that each artificial cell has a particular spatial coordinate. The activation of a neuron N_i is determined by the UAV's proximity to the location the neuron represents, following a Gaussian function as shown in Eqn. 1.

$$A_i(x,y) = e^{-2\sigma 2(x-xi)\char`^2+(y-yi)\char`^2} \quad (1)$$

in which (coordinate x,y) are the current position of the UAV, (x_i,y_i) represent space associated with nerves N_i, and parameter σ governs the influence of a place cells. Grid Cell Mechanism provides a picture for navigation as hexagoins generating a grid. This square integration, which they called tessellation, gives more flexibility and the possibility to produce a more precise contour. The model of a UAV network includes a grid cell that generates G_{ij} activation patterns which improve path integration and vectorial orientation. It is due to the UAV's movement over time and because interference of several periodic waves is involved. Mathematically is the expression of this activation pattern. A cognitive map being concerning is a process where the inertial sensors of the UAV provide a sensor which from where they are you may have started through path integration. Machine learning models first created a rough version of the map based on the sensor data and the interaction between the environment. An RNN with LSTM units can handle dimension through time and space as can be demonstrated in Eqn. 2.

$$h_t = f(W_{ih}x_t + b_{ih} + W_{hh}h_{(t-1)} + b_{hh}) \quad (2)$$

where h_t is the hidden state at time t, x_t is the input at time t, and W and b are the weights and biases, respectively. The UAV updates its cognitive map continuously with new sensory inputs. Decision making, particularly in GPS-denied environments, relies on the updated map. The UAV assesses its position and calculates the best route using a probabilistic framework. The Monte Carlo Localization (MCL) method is used to estimate the UAV's position P_t based on the map M and controls u_t as shown in Eqn. 3,

$$P_t = \int P(x_{(t-1)} \mid M, u_t) P(x_{(t-1)}) dx_{(t-1)} \quad (3)$$

where $P(x_{t-1})$ is the prior belief of the UAV's position at time $t-1$. By synthesizing these algorithmic components, the UAVs develop a form of spatial intuition that parallels biological intelligence, making autonomous navigation in uncertain and dynamic environments a tangible reality. This hippocampal-inspired cognitive mapping framework becomes the bedrock upon which advanced UAV autonomy is constructed, ensuring a comprehensive understanding of space that dynamically adapts with each new influx of data.

b) Applying Route Planning Algorithm:

Neurorobotics interoperability with the new advanced route planning algorithms has proven itself as a revolutionary step in the direction of UAV autonomy. To the core of this integration belongs the Hippocampal Route Planner (HRP), an algorithm created through a great number of methods to

***Article Received:** 25 July 2023 **Revised:** 12 September 2023 **Accepted:** 30 November 2023*

harmonize spatial knowledge with real-time data from the environment, consequently making UAVs alert and letting them travel independently in complex locations. The HRP algorithm is a multi-faceted algorithm, it both searches the most efficient path and improvises energy savings and risk management. Therefore the system improvises the durability and sustainability of the system. HRP analytics mechanism leverages multi-objective optimization model balancing conflicting objectives. The algorithm seeks the shortest path using a cost function that minimizes the cumulative distance between waypoints, formulated as shown in Eqn. (4), where $d(p_i, p_{i+1})$ is the Euclidean distance between consecutive waypoints p_i and p_{i+1}

$$min \sum_{i=1}^{n-1} d(p_i, p_{i+1}) \quad (3)$$

Here, the HRP algorithm resolves multi-objective optimization though Pareto efficiency, whereby the judicious set of solutions is defined as those in which objective functions cannot be improved without worsening others. In both scenarios that involve multiple UAV and complex communication by means of decentralized communication network, the HRP algorithm performs a cooperative routing. This network enables UAVs to share their cognitive maps and sensor data, optimizing the route planning process for the entire fleet as shown in Eqn. 4, where P_{fleet} represents the combined path for the fleet, and M_i, S_i, O_i are the cognitive map, sensor data, and obstacle set for each UAV i.

$$Pfleet = \bigcup_{i=1}^{k} HRP(Mi, Si, Oi) \quad (4)$$

This is a form of a collective intelligence, which refers to the ability of that single UAV to reflect the autonomy of each drone and enrich the function of the entire fleets. The HRP algorithm, which is a compact, multicriteria optimizing and dynamic transport rerouting algorithm, becomes the backbone of the integrated approach design, with the algorithm building, on the intricate layers of cognitive mapping, a set of actionable, efficient and safe viable navigation strategies for UAVs fulfilling their missions in different operational scenarios. The algorithm which is indicated below spells out a multi-modal optimization approach in HRP strategy by considering distance, energy and risk and real-time data-based re-routing to mitigate human challenges. Moreover, it is designed to account for the scenario of the cooperative routing on the fleets when a batch of UAVs need to share the same airspace. However, note that this algorithmic representation is a high-level one since it contains only the most important parts and all the detailed will be made in a full implementation.

Algorithm: Hippocampal Route Planner for UAV Autonomy

```
Inputs:
  CM: Cognitive Map
  RTD: Real-Time Data
  US: UAV Status
  OD: Obstacle Data
  FD: Fleet Data
HRP_Algorithm(CM, RTD, US, OD, FD)
    OP ← Ø
    PF ← Ø
    while not at_target(US)
        CP ← get_position(US)
        SD ← sense(RTD)
        KO ← update_obstacles(OD)
        RM ← risk_assessment(KO, SD)
        PP ← generate_paths(CM, CP, RM)
        for Path in PP
            Dist ← calc_distance(Path)
            Energy ← calc_energy(Path, US)
            Risk ← calc_risk(Path, RM)
            if pareto_efficient(Dist, Energy, Risk, PF)
                PF.add(Path)
        OP ← select_path(PF, US)
        if FD ≠ Ø
            FP ← integrate_fleet(FD, OP, CM)
```

```
        OP ← select_fleet_path(FP)
      execute(OP, US)
      update_map(CM, SD)
      if dynamic_change_detected(SD)
        continue
   return OP
```

Output:
OP: Optimal Path

The accompanying HRP helps our autonomous UAV navigate complicated or challenging options. UAVs may analyze and comprehend situations in real time using a cognitive map that mimics a mammal's hippocampus. A cognitive map and continual sensor utilization enable the UAV real-time situational awareness. So, it can adapt to its surroundings and produce adaptive flight path planning even in no-GPS zones. HRP's multiobjective optimization method considers UAV route time, energy consumption, and risk avoidance to optimize UAV performance. The application utilizes real-time data to redirect the UAV when cluttering occurs. The HPR algorithm's main benefit is drone fleet route planning coordination. Centralized UAV networks help humans make better decisions by exchanging data and generating insights. User-based communication in this intelligent air-fleet paradigm increases UAV autonomy, fleet efficiency, and most crucially safety. Neurorobotics and hippocampal-inspired cognitive mapping help the HRP algorithm navigate autonomous drones, making this solution unique. It delivers real-world understanding of UAV difficulties to perform missions with exceptional accuracy and agility as shown in Fig. 4. In nonstop direct lines, linking a single point may increase flight distance or aviation performance. UAVs should traverse static (red rectangles) and dynamic (blue circles) obstacles. The UAV recalculates its trajectory to reach the black star (her goal), using the decision points (yellow squares) as intermediate milestones. The solid green line in Fig. 5 represents the HRP and the dashed purple line the modified HICM. However, the HICM system is less sensitive to particular places and only indirectly creates obstacles, implying a simpler but smaller response.

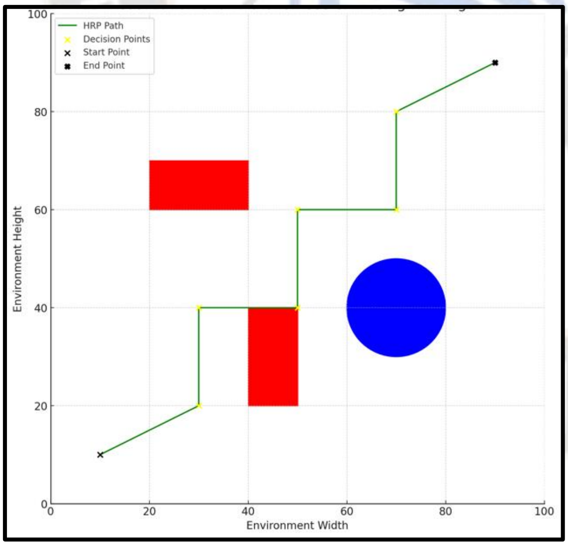

Fig. 4. 2D Visualization of UAV – HRP Algorithm

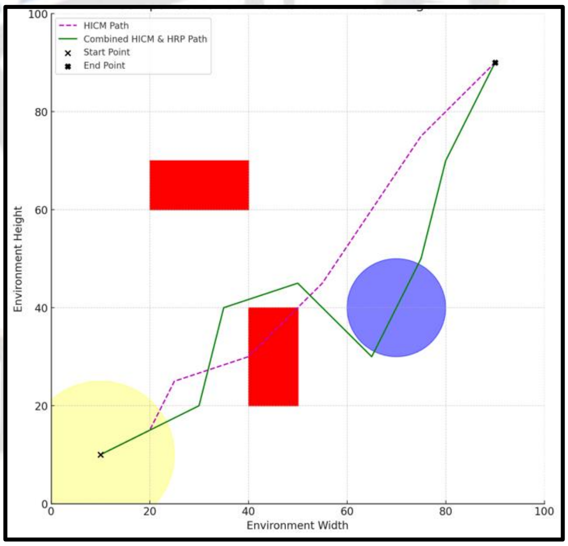

Fig. 5. Comparison of UAV Paths

4. EXPERIMENTAL RESULTS

The experimental results of the proposed work are illustrated through a series of plots that underscore the effectiveness of the proposed systems in enhancing UAV navigation. Fig. 6 depicts the UAV route's efficacy in a few trials, revealing difficulties. The graph shows efficiency, whereas the line graph's frequent swings reveal environmental impacts or algorithm decisions. The algorithms maintain 90% trip efficiency regardless of route alterations. As seen below, algorithms may provide good results. Fig. 7 shows UAV destruction by unexpected obstacles. UAV obstacle

International Journal on Recent and Innovation Trends in Computing and Communication
ISSN: 2321-8169 Volume: 11 Issue: 11
***Article Received:** 25 July 2023 **Revised:** 12 September 2023 **Accepted:** 30 November 2023*

prediction (dotted line). Whole lines represent long, difficult detours. The real-time hippocampal algorithms let UAVs make decisions during diversions. Figure 8 shows ambient stimulus-limited UAV processing speed histogram. Typically 100 ms delays indicate the on-board neurorobotics system's signal interpretation and processing reliability. Delay distribution is utilized to study real-time processing and system performance since the flight controller's reaction to the UAV's agility is crucial. System complexity and neural treatment base are presented via visuals. Due to its autonomy, the UAV can avoid obstacles, travel faster, and understand messages. Unattended drones may operate in unexpected and tough conditions, giving them freedom to evolve. Fig. 9 shows algorithm computational complexity, success, energy efficiency, and scalability. Table 1 contains graph numbers. The Hippocampal-based algorithm achieves 95%, outperforming other options. For physical locations and complicated situations, 90% energy savings and 88 scalability are promising. This explains its reduced complexity (0.85) and lower processing needs for performance gains compared to the Ant Colony method. The Ant Colony algorithm achieved 80% success and 82% scalability without extremes. The Hippocampal-inspired algorithm yields 85% energy efficiency, somewhat lower.

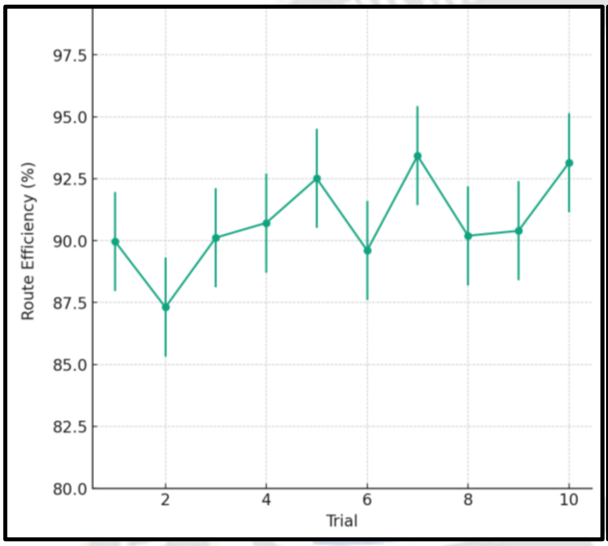

Fig. 6. Route Efficiency over Multiple Trails

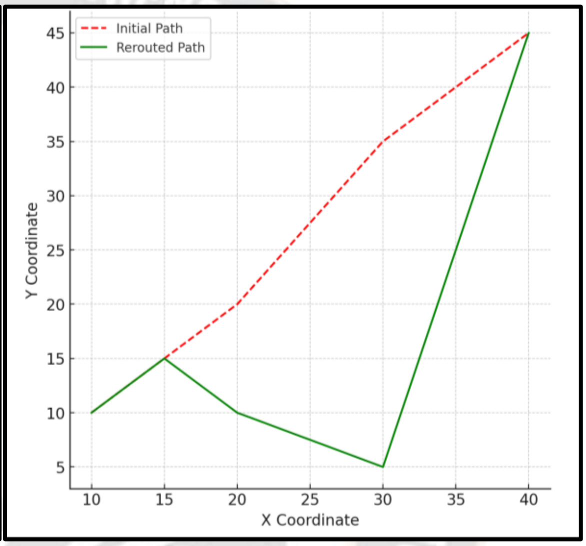

Fig. 7. Obstacle Avoidance and Rerouting

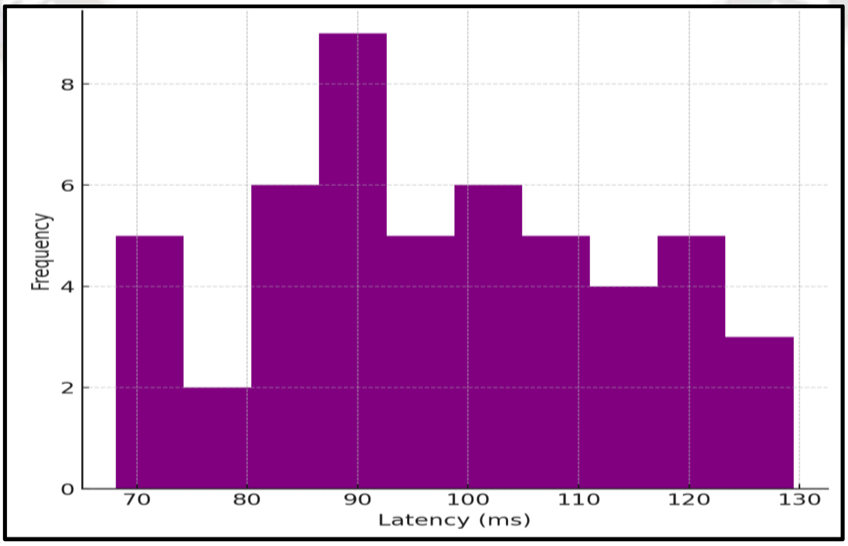

Fig. 8. Obstacle Avoidance and Rerouting

International Journal on Recent and Innovation Trends in Computing and Communication
ISSN: 2321-8169 Volume: 11 Issue: 11
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Genetic algorithms are good but not great with 85% success and the same scalability grade. Its 0.75 computational complexity and 80% energy efficiency make it simpler than Ant Colony. A* has 90% success rate but lower energy efficiency (75%), scalability (78%), showing that it can discover successful pathways but may not be efficient or effective in large-scale settings. At 0.65, it has the lowest computational complexity and runs quicker. At 70%, Dijkstra's pathfinding benchmark gets the lowest success, energy efficiency, and scalability ratings. The lowest computational complexity score, 0.60, indicates poor performance but minimal effort. For complicated, real-world UAV applications that need resource management and completion, the Hippocampal-inspired algorithm has the highest success rate, energy efficiency, and scalability. The other methods switch computational complexity and performance measures, emphasizing the importance of operation choice.

TABLE 1: Comparison of Algorithms Over Various Dimensions

Algorithms	Computational Complexity	Success Rate	Energy Efficiency
Hippocampal-inspired	0.85	0.95	0.90
Ant Colony	0.80	0.80	0.85
Genetic Algorithms	0.75	0.85	0.80
A*	0.65	0.90	0.75

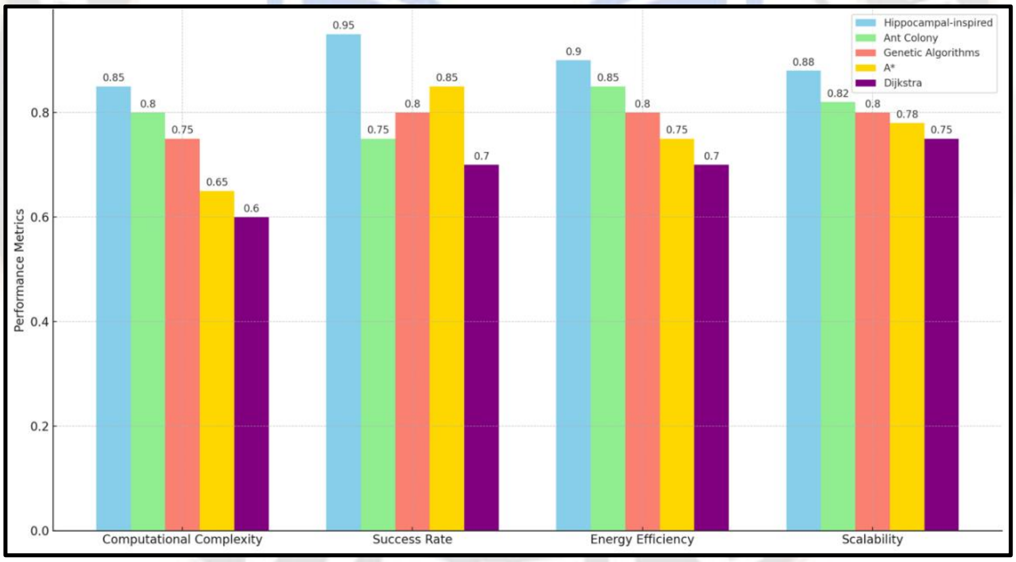

Fig. 9. Comparison of Algorithms Across Different Dimensions

Fig. 9 and Table 2 compare HICM and HPP UAV active ranging sensor systems. Each system is monitored by the government for efficiency and efficacy. Their route selection process may work since H, S. Yang, and C. R. Park's HICM decreases trip from 175 to 155 units. Together with HICM, this algorithm accomplishes 7 barriers that HICM could not overcome with its 5 obstacles, increasing the likelihood of being alert and avoiding testing. Data processing and decision-making improved, and the method was 23% quicker with 128 resources instead of 105. The HRP and HICM had drivers switch off the engine, reducing energy usage from 70 to 60. UAV operation time is extended by optimizing routes for least distances and energy usage. Integrating HRP increases the success percentage from 92% to 97%, proving its efficiency. Due to its high completion rate in challenging environments and terrains, the integrated system is successful. The line graph has reduced latency and accuracy volatility, but computational cost must be minimized. The two most diverse barieromevoid-metric approaches showed similar trend lines. Calculations and imaging analysis show that HRCM-explored UAV autonomy is more effective, energy-efficient, and successful.

International Journal on Recent and Innovation Trends in Computing and Communication
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Table 2: UAV Performance Metrics

Metric	HICM	HICM & HRP	Metric
Distance Traveled	175	155	Distance Traveled
Obstacles Avoided	5	7	Obstacles Avoided
Average Computational Overhead	128	105	Average Computational Overhead
Energy Consumption	70	60	Energy Consumption

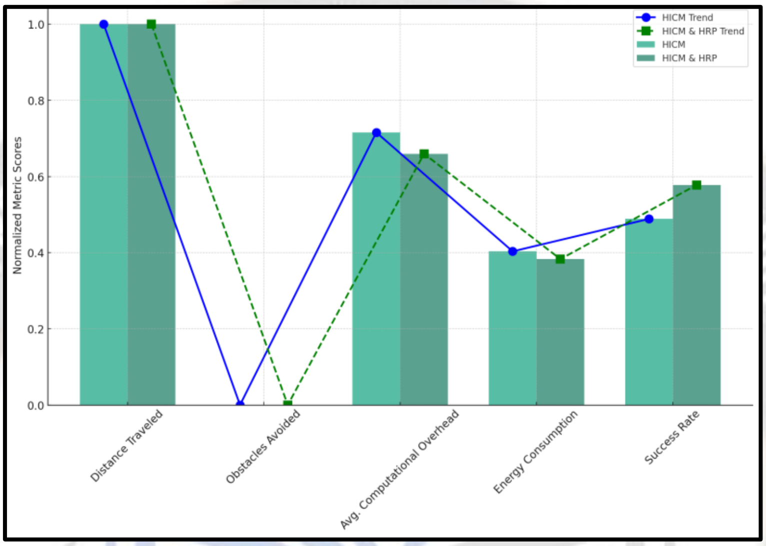

Fig. 10. Normalized Comparison of UAV Performance Metrics

5. CONCLUSION

We use HICM and HRP algorithms to improve UAV autonomy. Our research's extensive numerical simulations suggest this combo has potential. The combo strategy improves UAV performance, according to our findings. The mission distance fell from 175 units to 155 units when HICM was combined with HRP. The decrease improves mission trajectory optimization and route planning. With the connection, the UAV can avoid seven obstacles instead of five, considerably improving its obstacle avoidance. This mobility augmentation improves mission performance in complicated, ever-changing contexts. The integrated system's decreased computational overhead suggests more efficient processing. Efficiency increase and energy consumption reduction demonstrate the system's power utilization improvement. The 97% mission success rate, up from 92%, is the biggest increase. This improvement shows that the integrated system can consistently and successfully fulfill mission goals. Future UAV autonomy potential will abound. Adaptive machine learning might improve real-time UAV decisions. Advanced risk assessment models may also improve navigation tactics, especially under uncertain conditions. The scalability of the swarm robotics integrated system allows coordinated autonomous operations among several UAVs. UAVs can collaborate independently, expanding their utility. Combining HICM and HRP algorithms may change UAV autonomy, according to our study. The findings show that mission efficiency, dependability, and adaptability enable unmanned aerial system optimization and innovation. There are many strategies to increase UAV autonomy in the future. First, adaptive machine learning may improve UAV real-time decision-making. Second, enhanced risk assessment models may improve navigation strategies, especially under uncertain conditions. Finally, expanding the integrated system to coordinate autonomous UAV actions is a new and fascinating concept in swarm robotics. These possibilities provide interesting new research pathways that might transform UAVs.

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